A Novel Model to Predict the Whack of Pandemics on the International Rankings of Academia

Nidhi Agarwal[1,2] and Devendra K. Tayal[1](✉)

[1] Indira Gandhi Delhi Technical University for Women, Delhi, India
devendrakumartayal@gmail.com
[2] Delhi Technical Campus, Greater Noida, India
http://www.delhitechnicalcampus.ac.in

Abstract. Pandemics bring physical life to a complete standstill; people are bound to remain confined to their homes. Students suffer a lot academically due to closure of educational institutes worldwide due to pandemic fear. In such a scenario, imparting adequate education to them so that their academics is not affected, is a big challenge. During the COVID-19 pandemic time, educational institutions have really played a good role in imparting online education to students. Their career and academic tenure were not affected. It is contrary to the past pandemics throughout the world history where students' academic years were lost. All this has been possible because of advancement in technologies related to Human Computer Interaction. The educational institutions tried to cope up a lot with the current educational mode but lacked in some or the other international ranking parameters. This brought sudden dips in their international ranks which can be regained only in long periods of time with major extra efforts. This research work provides an insight on the slipped off international ranks of higher educational institutions during global disruptive conditions like pandemics (COVID-19 and combatting with future pandemics). The novel model proposed in this work helps academicians in predicting the impact of pandemics on their overall international rankings so that recovery decisions and plans can be taken timely by academicians to combat with the situation. The work involves developing a model based on Machine Learning advanced algorithms with the inclusion of a humongous ranking dataset. Strong empirical results support the high efficiency as sensitivity = 97.98, Accuracy = 97.54, F1 value = 97.82, Kappa-score = 0.95. Using the proposed model. To the best of our knowledge, till now none of the researchers have proposed any such pioneering tool for academicians using advanced Machine Learning algorithms.

Keywords: University rankings · COVID-19 · Pandemics · Machine Learning Models · Higher Educational Institutions

S. Nandan Mohanty et al. (Eds.): ICISML 2022, LNICST 471, pp. 24–38, 2023.
https://doi.org/10.1007/978-3-031-35081-8_3

1 Introduction

Past pandemics in the world history brought academia to a complete standstill. There were huge academic losses to students in the form of year loss, zero-education, delayed admissions and even no admissions. But the academia industry played completely different role during the current pandemics “COVID-19”. The sole credit goes to advancement in technologies related to Human Computer Interaction. Students were connected virtually to their schools, classrooms, teachers and most importantly with their peers [1–4]. The technological advancements even provided them ways to attempt quizzes, assignments, tutorials etc. both graphically and textually. Even the video-call based applications provide students with the facility to keep their classroom-customised background where they can have a complete classroom feel [5–8]. All this lead “COVID-19” not hamper the students’ higher level academia. All this could help educational institutions to continue their aacademia uninterruptedly but there were various factors at the international level which were neglected during the pandemics. These are those factors which actually contribute for the international ranking of the various higher educational institutions (HEIs). A large chunk of students which comes from various other countries known as “international students” was unable to be catered by all the academia.

There are various Australian and European countries whose major chunk of student contribution is from the international market. The universities of these countries were affected badly by the closure of borders. They were unable to cater the international students which remarkably reduced their international ranking scores. In this way, a major ranking parameter which is dependent on “international students” was undoubtedly reduced. The various other factors related to publications, citations, visits as resource persons in various other academia which have a great contribution in the international ranking parameters were also hampered. The various educational institutions dealing with traditional modes of education were completely neglected by the admission aspirant student community. The new entrants were totally unwilling to take admission in traditional educational institutions. Various HEIs demanding higher fees were also neglected by the new student community. As we all know that the privately owned educational institutions are dependent mainly on the fee which they get from students, so their growth and their stay in international market were also hampered. Finance also plays a major role in the advancement of any educational institution because it has a major contribution for procuring new tools, technologies, softwares and infrastructure. All this lead to significant reduction in the ranks of various educational institutions especially if we talk about the privately owned ones. This work would provide an insight to combat with current and future pandemics regarding Higher Educational Institutions students. The study involves only those working professionals who are pursuing higher studies also.

2 Overview of the Related Work

At the very onset of year 2020 the various HEIs were forced to go for online mode of education with a sudden shift from the offline one. This forced the educational institutions to put their major emphasis and energy on how to accelerate the new mode of education.

All the resources, energy, time, resources were consumed in implementing this mode of education in a proper and best possible manner. Due to this, the various parameters on which the institutions and academicians used to focus during pre-pandemic times to gain higher rankings was neglected. Also, the number of students being catered as "international students" was reduced significantly due to the physical closure of the universities. As during the pandemic time people suffered from a lot many financial losses so continuing or opting for high fee based educational institutions for their wards proved to be quite difficult for majority of the parents. In such a scenario even in developed countries like United States, according to the study [9], the parents preferred not to opt for very high fee demanding higher educational institutions. In most of the high fee demanding higher educational institutions the enrolment ratio even dropped to half during the 2 years of pandemics. These universities which were affected majorly by the COVID-19 pandemic. In the absence of adequate finances, the universities were unable to maintain many parameters for sustainability in the international ranking fight. Even if we look at the various highly reputed Australian, American, or European universities, many of them had to face these challenges [10, 11].

The Australian and the European universities were majorly affected by this pandemic scenario and faced a significant dip in the international rankings [12, 13]. Lack of adequate finances which comes majorly from the "international student" cult stopped them from taking various progressive steps which can compete them in the international market [14, 15]. The Australian universities have highest number of international students in their campus. According to a report for these universities the international students contribute to even 1/4 of the total number of enrolments in Australia in the years prior to COVID-19. But this percentage dipped significantly during the post COVID time and reduced to even 2% to 3% for the years 2020 and 2021 enrolments 9 [16, 17]. As these are the major countries which faced pandemic to a greater extent and lockdown continued in these countries for a longer duration and so the quarantine period. So, the campuses were almost deserted with minimal enrolments as discussed above. If we see the pre-pandemic scenario for these countries, then the enrolments for the masters and the doctorate degree programmes were even higher as compared to that for graduate degree programs [18, 19]. It summarises that during the pre -pandemic times, the enrolments were fairly good for the graduate programs (around 25%) but they were excellent for the postgraduate and doctorate programs (reaching even up to 50% of the total enrolments) [12].

If we talk about the Indian students who used to take admission in China based HEIs by the year 2019, then it was around 60% but during the tenure of pandemics, this value reduced even to 10% to 15% [18]. According to an Australian universities survey, around 6500 academicians lost their jobs during the pandemics because of lesser turn ups of students in higher educational institutions, this data even involves some of the best Australian universities [30]. In this context, China also faced significant financial losses because of the early outbreak covid in China as well as due to long duration of covid restrictions due to closure of international borders [20].Their academic business process model has been shattered because of the pandemics. The money from international students, which was used to raise the rankings of the universities, could not be generated [19]. Many senior academicians anticipate that if the same condition prolongs for one or two more years, then major Australian universities will have to lower their academic standards in various parameters which would substantially impact the international ranking scores [23]. This is a very alarming situation which needs to be addressed especially for Australian based universities.

The research fundings have also been reduced which has led to the reduction in thousands of research-oriented jobs for the Australian universities, which has again significantly reduced their international rankings. To combat with this situation many of the Australian best universities have started switching to the short-term courses (with the help of some local educators) and online lectures in partnership with the local people. But this has no not been able to solve the problem entirely. All this has no doubtedly impacted educational standards and thus also impacted the overall international ranking of these institutions. This will take a long time to help these universities regain their international stay in the academia market. Academicians also fear that the top universities may permanently lose their international rankings as would not be able to recover themselves at all with these alarming situations. If we talk about UK based higher education institutions, then they have comparatively low ratio of "international students" as compared to Australia based universities. But they have a good contribution of "international students" as compared to various other countries of the world. The major turn-ups for these UK based universities are for bachelor's and master's degree programs [24]. Europe has always offered very high scholarships which has attracted good percentage of international students[25]. This has been the prime attraction among the international students to opt for these universities. But during the pandemic, even after offering scholarships the students had not turned up to the mark. The major reason behind this goes to the closing of international borders[24]. Various parameters on which these universities work come from the student contribution in which the mixed knowledge sharing and working on interdisciplinary projects by the mixture of international and national students matters a lot. But this collaboration reduced significantly because of the above stated reasons[27].

Most of the UK based HEIs depend majorly on the funds given by the government [27, 28] but during the pandemics, these funds have been reduced which led to a great dip in the international ranking scores for these universities. The recruitments were also affected a lot because of the pandemics. This restricted students to not opt for the satisfactory jobs as they were deserving. The layouts of the staff and the faculty members has also taken place to a great extent during these times due to which academic retention ratio has been reduced which is a major contributor in the international rankings of most of the ranking bodies. All these reasons discussed about various universities in the world, be it public sector or private sector based, higher ranking based, or lower ranking based, their rankings dipped significantly during the pandemics. The fear is that many of these universities will take years to combat with the situation and few of them might not even be able to recover themselves for longer duration. This is a bitter fact which most of the academia has faced during the pandemics.

3 Proposed Methodology and Design

The dataset used in the research work is taken from the Kaggle repository and contains a vast collection of international ranking parameters data of various academia of 5 years viz for years 2017–2022. This includes the data of all reputed HEIs which have been able to place themselves in the international ranking fight for last 5 years including the current year 2022.The data comprises of total 6482 universities for 5 years out of which 1368 are distinct universities at international ranking level. The dataset contains 6482 rows and 15 columns. The various parameters on which these universities are categorized are the research output from faculty, students and staff faculty student ratio, number of international students, size of the university, the count of the faculty members. As is indicative from these parameters that research plays a very important role in the international ranking of various educational institutions. The number of faculty members per specified number of students also contributes a lot to the same. No doubt the number of "international students" taking admission in any higher educational institution in a particular year also contributes a lot for international rankings. As is indicative from the data through the data set that the number of international students has dipped considerably during the pandemic years. All this will be discussed in detail in Sect. 4 in the results part.

The universities are categorised as public sector based at private sector based. The research output is taken in 3 categories as high, low, and very high. The university size is taken as small, large, extra-large. Faculty count is also of great importance in contributing to the international ranking parameters of the university. The proposed methodology is shown in Fig. 1, as we can see that the first step is to load our database which is in the form of a CSV file to the pandas data frame. Then we divide the data set into the training and test datasets to make the predictions. Usually, the preferred values to divide the training and the test dataset is 70% and 30%. As the data is quite humongous which is running in thousands of number of rows and tens of columns, so it may be possible that some of the data values are missing. Thus, an important part is to check for the missing data which is done as the next step. Then we go for the data pre-processing where we first normalise the data to bring it to a uniform scale and then deal with the imbalanced data problem. Imbalanced data refers to the presence of outliers in the dataset for a particular attribute. The presence of outliers makes the predictions biased, so we need to handle and remove it properly so that our predictions are not affected. Then, finally we deploy the model based on the proposed approach.

Here the approach which we are using to deploy the model is a computationally strong, effective, and efficient supervised machine learning supervised model called XGBoost model. This model has a very high predictive power and thus has been adopted as our proposed methodology. The various other models were also tried but the results generated by them were not so satisfactory. So, we have adopted this XGBoost model-based approach in our proposed methodology. It is a computationally strong model and is capable of dealing with humongous amount of data. Then after the model deployment the predictions are made to check the efficacy of the proposed model. Then a comparative analysis is made to depict the comparison of the proposed model with the various other approaches. Then finally the model is evaluated on the basis of various important parameters to ascertain the enhanced predictive power generated using our proposed approach. The various steps followed by the proposed methodology are summarised below.

3.1 Loading the Dataset

The data is present in various formats in the dataset. It may be a text file format, excel file or a comma separated file. The data is loaded in csv format using Python pandas and the required function readcsv will be used to load and retrieve data from the pandas dataframe. The data is loaded in the form of a 2D matrix.

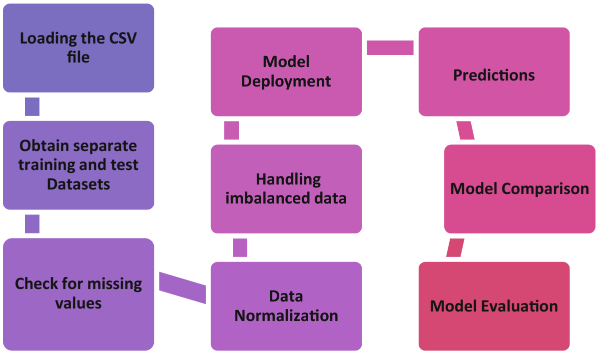

Fig. 1. Proposed Methodology

3.2 Splitting the Dataset

After loading the dataset, one needs to break it down to corresponding training and testing components. The training component gives inputs to out prediction model while the testing component checks for the efficacy of the proposed model. The aim of machine learners is to produce higher efficacy models on the basis of various important parametric attributes.

3.3 Data Pre-processing: Checking for Missing Data

Since we are dealing with a humongous dataset which comprises of total 6482 universities for 5 years out of which 1368 are distinct universities at international ranking level. The dataset contains 6482 rows and 15 columns. The various parameters on which these universities are categorized are the research output from faculty, students and staff faculty student ratio, number of international students, size of the university, the count of the faculty members. There are possibilities of missing data values in various blocks. To deal with this situation, one needs to devise methodologies so that the meaning of data is not affected.

3.4 Data Pre-processing: Data Normalization

The data many a times needs to be normalized to bring it to a uniform scale. This helps in making the predictions more easily and efficiently without even changing the meaning of data.

3.5 Data Pre-processing: Handling Imbalanced Data

Sometimes the data is quite imbalanced, some major values belong to one class and minor to another class. Data imbalance may also be observed with multiclass where some classes contain many output categories and others contain lesser values. This makes the predictions biased and thus the overall efficiency of the model may be reduced. We have many ways to deal with it, out of which the solution adopted by us is SMOTE analysis (Synthetic Minority Oversampling Technique).

3.6 Deploying the Proposed Model

Finally, we deploy the model based on the proposed approach. Here the approach which we are using to deploy the model is a computationally strong, effective, and efficient supervised machine learning supervised model called XGBoost model. This model has a very high predictive power and thus has been adopted as our proposed methodology. The various other models were also tried but the results generated by them were not so satisfactory. So, we have adopted this XGBoost model-based approach in our proposed methodology. It is a computationally strong model and is capable of dealing with humongous amount of data.

3.7 Make Predictions

The proposed model is used to make predictions whether during the pandemic time, the international rankings of various HEIs all over the world dipped or not. All major international ranking parameters are considered and 1368 universities at international level are considered for a span of 5 years. So, in total 6482 values for universities are used for 5 years data from year 2017–2022. The fit () function from XGBoost Classifier-model fits model by taking 2 input values as set of input variables which are used to make predictions and the end-target variable. Here the input variables comprise of those attributes which depict the underlying features of that attribute. In this work, the following attributes in the dataset describing the various ranking parameters for past 15 years act as input values.

Type of University
Research Output
Student-Faculty Ratio
International Students
Size of University
Faculty Count
Total Score

Here the "**Total score**" describes the sum total of the quantitative measure based on above metrices. All the above metrices are either categorized as numeric or non-numeric. The numeric metrics are added directly by multiplying them with their corresponding weights. Corresponding weights are obtained based on a particular international ranking criteria. The non-numeric attributes are first converted to some pre-specified numeric values, and then added to the total score by multiplying with the corresponding weights. The conversion factor and corresponding weights are also obtained based on a particular international ranking criteria.

3.8 Model Comparison with Other Models

Then a comparative analysis is made to depict the comparison of the proposed model with the various other approaches. As we can see in Sect. 4 that the various other models are not generating satisfactory results in terms of various parameters as compared to the proposed model.

3.9 Evaluate the Model

The proposed model is evaluated on the basis of various parameters like accuracy, sensitivity, specificity, f1-value, kappa-statistics etc. The empirical results for all the important parameters will be discussed in Sect. 4. These results ascertain the enhanced predictive power generated using the proposed model as compared to the other models.

The various attributes on the basis on which the model is evaluated are depicted in Table 1. A (2*2) matrix called the confusion matrix is depicted in Table 1 which shows the binary classification in the form of values 0 and 1, where 0 represents those universities, whose ranks didn't dip during the two academic years effected by pandemics viz 2021 and 2022. The value 1 represents those universities which did not account for dipped ranks during two pandemic effected academic years. The various parameters deciding the predictive power of the proposed model are discussed in detail in Table 1.

Table 1. Evaluative Parameters

		Actual output values	
	Total values	**Positive Condition**	**Negative Condition**
Predicted output values	**Predicted values match**	**TP (*Correctly identified universities whose ranks dipped)***	**FP (*Incorrectly identified universities whose ranks dip)***
	Predicted values don't match	**FN *(Incorrectly identified universities whose ranks didn't dip)***	**TN *(Correctly identified universities whose ranks didn't dip)***
	$Precision = \frac{TP}{TP + FP}$	$Recall\ or\ Sensitivity \frac{TP}{TP + FN}$	$f1 - score = 2 * \frac{Precision * Recall}{Precision + Recall}$

Here output values are those which decide whether the ranks dipped or not during 2 pandemic years of academia. The various other attributes like accuracy, precision, recall, True_positives, False_positives etc. are calculated according to the formulae shown in Table 1. The Table 1 also contains the elaboration of these attributes. The TP (True_Positives) define the number of those HEIs which are rightly identified by the proposed model that their ranks have dipped during the pandemic academic years. The FP (False_Positives) define the number of those HEIs which are wrongly identified by the proposed model that their ranks have dipped during the pandemic academic years. The FN (False_Negatives) define the number of those HEIs which are wrongly identified by the proposed model that their ranks haven't dipped during the pandemic academic years. Similarly, the TN (True_Negatives) define the number of those HEIs which are rightly identified by the proposed model that their ranks haven't dipped during the pandemic academic years. The various other measures are calculated on the basis of these 4 measures only according to.

4 Empirical Setup with Implementation Details

The proposed model is used to make predictions whether during the pandemic time, the international rankings of various HEIs all over the world dipped or not. All major international ranking parameters are considered and 1368 universities at international level are considered for a span of 5 years. So, in total 6482 values for universities are used for 5 years data from year 2017–2022. The fit () function from XGBoost Classifier-model fits model by taking 2 input values as set of input variables which are used to make predictions and the end-target variable [29–31]. Here the input variables comprise of those attributes which depict the underlying features of that attribute. In this work, the various attributes in the dataset describing the various ranking parameters for past 15 years act as input values are Type of University, Research output, Student-faculty ratio, Number of International students, Size of University, Faculty count and the total score.

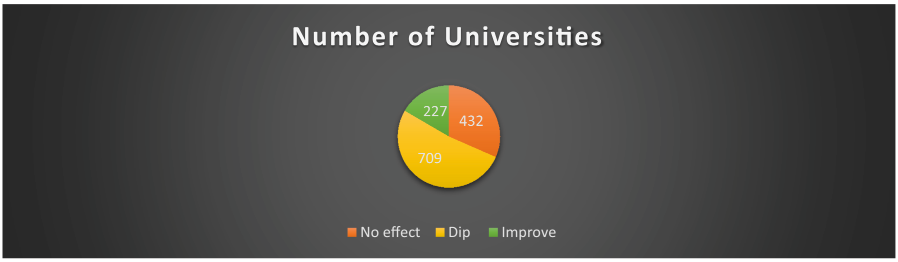

Fig. 2. Number of universities whose ranks Dipped, Improved, remained same during COVID

As is evident from Fig. 2 that the total number of universities is 1368 out of which 227 improved their rankings during the pandemic academic years, 432 maintained their rankings consistently before and after pandemic and there was many 709 which is approximately 50% of universities whose ranks dipped considerably during pandemic academic years. This is a big number which majorly forced us to provide a solution to such HEIs through this research work. All the HEIs are categorized as private and public universities. As is evident from Fig. 2 that out of total, 13% are privately owned and 87% are publicly owned and the dip is not related to this category. One can easily deduct from Fig. 4 that the universities in our dataset, which fight for international ranks, have been consistently able to maintain highly satisfactory faculty student ratio. The majority of universities i.e. more than 50% are able to maintain the ration in the range 1–10. Around 35% maintain the ratio from 11–20 (Fig. 3).

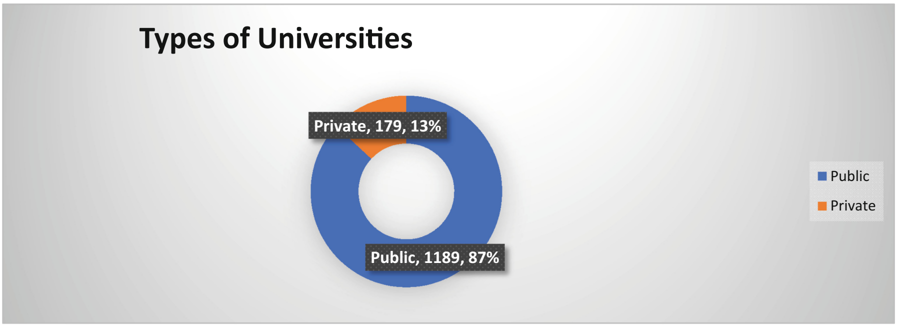

Fig. 3. Types of universities

And the remaining 15% contribute to ratio higher than 20. This value is quite satisfactory from the university and more importantly from student point of view as they get more individual attention from their teachers.

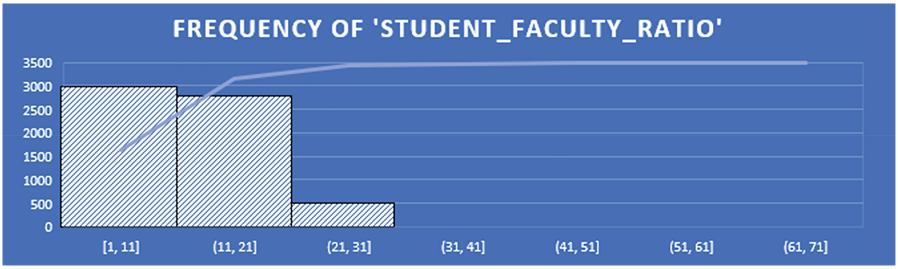

Fig. 4. Student-faculty ratio frequency

Another major attribute is the "research output" which is categorized into 4 attributes viz "Very High", "High", "Medium" and "Low". As is quite clear that the research has a strong contribution in the total score of all the national and international rankings bodies. The higher the research contribution, the greater would be the "total_score" leading to higher rankings. As is very clear from Fig. 5 that 4586 out of 6482 values in the dataset account for "Very High" research output. It implies that all these are research intensive universities.

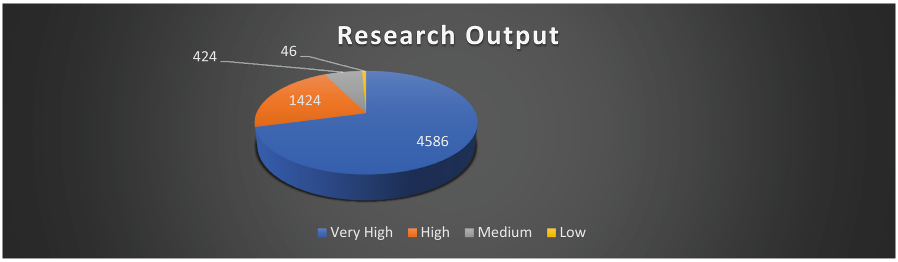

Fig. 5. Number of universities having various categories of Research Output

But even during the pandemic years, many of these highly research intensive HEIs were unable to maintain their academic ranks. It is due to reduction in various parameters which are governed by closure of physical international borders. The main attribute which got reduced which in turn reduced the ranking of many institutions was drastic reduction in the number of “international students”. The same is also evident from Fig. 6, one can notice a drastic downfall in the number of newly admitted students during pandemic years. One can easily deduct from Fig. 7 that the dataset which is being used in this research work is quite vast. It caters to all the types and categories of universities. Based on the count of students, the HEIs are categorized as “Extra Large”, “Large”, “Medium” and “Small”. The maximum percentage is for “Large” category of universities. Then is the percentage of universities with “Extra Large” size.

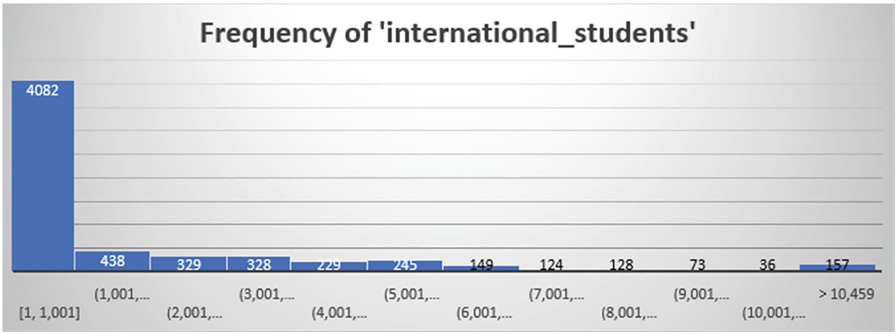

Fig. 6. Frequency of international students

The Table 2 shows the predictive values obtained using the proposed model by adopting XGBoost model for making the predictions. The various values are as ***Specificity = 98.56, Sensitivity = 97.98, Accuracy = 97.54, F1 value = 97.82, Kappa-score = 0.95.*** The values of various parameters are quite satisfactory. We have been able to achieve higher values for accuracy which is 97.54%. This value is achievable using the proposed model only. As will be discussed in next section, these high predictive values are obtained using the proposed model only. For other machine learning models, the obtained values are comparatively lower. A comparative analysis for the same is also available in next section in tabular and bar graph form.

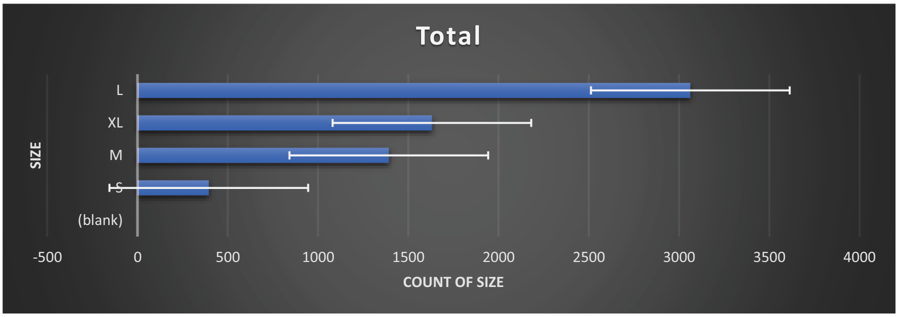

Fig. 7. Size of universities

Table 2. Statistical Parameters Obtained Using Proposed Model

Model Adopted	Specificity	Sensitivity	Accuracy	F1-value	Kappa-score
Proposed Model	**98.56**	**97.98**	**97.54**	**97.82**	**0.95**

5 Collating with State-of-Art

If the proposed model undergoes prediction using Random Forest Classifier method, Logistic Regression and Naïve Bayes then the values of various statistical parameters are depicted in Table 3 and Fig. 8.

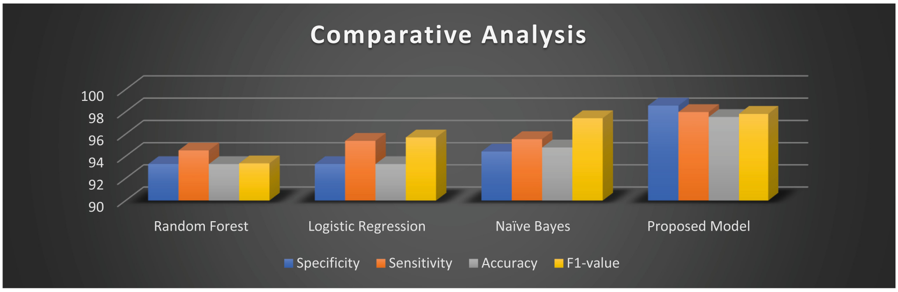

Fig. 8. Comparison of Proposed Model with other algorithms.

As is clearly indicative that using the proposed model, we can obtain the highest values for all statistical measures like ***f1-score, sensitivity, specificity, accuracy and kappa score.*** The bar graph showing a comparative analysis of all three models with our proposed model is shown in Fig. 8.

Table 3. Statistical Parameters' Comparative Analysis

Model Adopted	Specificity	Sensitivity	Accuracy	F1-value	Kappa-score
Random Forest	**93.3**	**94.53**	**93.3**	**93.37**	**0.78**
Logistic Regression	*93.3*	**95.4**	**93.3**	**95.7**	**0.87**
Naïve Bayes	**94.43**	**95.55**	**94.8**	**97.43**	**0.93**
Proposed Model	**98.56**	**97.98**	**97.54**	**97.82**	**0.95**

6 Deductions and Subsequent Work

In this paper, a novel model is proposed to help academicians in predicting the impact of pandemics on the overall international rankings as it is observed that due to physical closure of HEIs, their rankings dipped considerably. Through this research work, the recovery decisions and plans can be taken timely by academicians to combat with the situation. The work involves developing a model based on XGBoost Machine Learning model on the basis of a humongous international ranking dataset. Strong empirical results showed the high efficiency and accuracy of the proposed model. Till now none of the researchers have proposed any such pioneering tool for academicians using advanced Machine Learning algorithms. Though we have been able to obtain higher accuracy value of 97.54% using the proposed model, we can work in future to obtain even higher values for it. To achieve this, an ensembled model can be explored for implementation which involves more than one machine learning and deep learning models working together. The work cab be enhanced further in future by using deep learning models also for better predictive results. It can also be extended to all age group of students' studies.

References

1. Alhadreti, O.: Assessing academics' perceptions of blackboard usability using SUS and CSUQ: A case study during the COVID-19 pandemic. Int. J. Hum.-Comput. Interact. **37**(11), 1003–1015 (2021)
2. Callaghan, F.V.O'., Neumann, D.L., Jones, L., Creed, P.A.: The use of lecture recordings in higher education: A review of institutional, student, and lecturer issues. Educ. Inf. Technol. **22**(1), 399–415 (2017)
3. Park, S.W., Cornforth, D.M., Dushoff, J., Weitz, J.S.: The time scale of asymptomatic transmission affects estimates of epidemic potential in the COVID-19 outbreak. Epidemics **31**, 100392 (2020)
4. Scagnoli, N.I., Choo, J., Tian, J.: Students' insights on the use of video lectures in online classes. Br. J. Edu. Technol. **50**(1), 399–414 (2019)
5. Lwoga, ET., Komba, M.: Antecedents of continued usage intentions of web-based learning management system in Tanzania. Education+ training (2015)
6. Agarwal, N., Tayal, D.K.: FFT based ensembled model to predict ranks of higher educational institutions. Multimedia Tools Appli. **81**, 34129–34162 (2022)
7. Nguyen, N.T., Chinn, J., Nahmias, J., Yuen, S., Kirby, K.A., Hohmann, S., Amin, A.: Outcomes and mortality among adults hospitalized with COVID-19 at US medical centers. JAMA Netw. Open. **4**(3), e210417- e210417-e210417 (2021)

8. Marín, D.V., Cabero, A.J.: Las redes sociales en educación: desde la innovación a la investigación educativa. RIED. Revista Iboeroamericana de Educación a Distancia. **22** (2), 25–33 (2019)
9. Belkin, D.: Is This the End of College as We Know It?, in The Wall Street Journal (2020)
10. Duffy C.: Humanities degrees to double in cost as government funnels students into "job-relevant" uni courses. ABC News (2020)
11. Ratten, V.: Coronavirus (Covid-19) and the entrepreneurship education community. J. Enterprising Commun. People Places Global Econ. (2020)
12. Feuerlicht, G., Beránek, M., Kovář, V.: Impact of COVID-19 pandemic on Higher Education. In: 2021 International Conference on Computational Science and Computational Intelligence (CSCI), pp. 1095–1098. IEEE (2021)
13. Jackson, C.: DATA SNAPSHOT: 2019, Universities Australia (2021)
14. De, W.H., Adams, T.: Global competition in higher education: A comparative study of policies, rationales, and practices in Australia and Europe, in Higher education, policy, and the global competition phenomenon, pp. 219–233. Springer (2010)
15. De, W.H.: Trends, issues and challenges in internationalisation of higher education. Centre for Applied Research on Economics and Management, School of Economics (2011)
16. Update C. 11,965,661 Cases and 546,988 Deaths from COVID-19 Virus Pandemic-Worldometer. Доступно на (2020). https://www.worldometers.info/coronavirus/#countries.
17. AEN. Student Numbers at Australian Universities Australian Universities.com.au. (.2020) https://www.australianuniversities.com.au/directory/studentnumbers/
18. OECD. International Student in Australia Statistics - Study Abroad in Australia. (2019) 2019–12–13 https://www.studying-inaustralia.org/international-student-in-australia-statistics/
19. Ross, J.: Economic ramifications of the COVID-19 pandemic for higher education: a circuit breaker in Australian universities' business model? Higher Educ. Res. Developm., 1–6 (2020)
20. Ferguson, H., Love, S.: Universities and COVID – Parliament of Australia. (2020). (12 Oct 2020]. https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/FlagPost/2020/August/Universities_and_COVID
21. Ferguson, R.: Group of Eight warns of 'brain drain' with 7000 jobs set to go, in The Australian. 2020, News Corp Australia: Australia (2020)
22. Tertiary Education Quality and Standard Agency (TESQA). Key financial metrics on Australia's higher education sector (2018)
23. Ferguson, R.: Crisis leaves unis facing global crash: Craven, in The Australian (2021), @australian
24. Study Portal. Tuition Fees at Universities in Europe in 2020 - Overview and Comparison - MastersPortal.com. (2020). https://www.mastersportal.com/articles/405/tuition-fees-atuniversities-in-europe-in-2020-overview-and-comparison.html
25. Eurostat. Learning mobility statistics - Statistics Explained. (2020). https://ec.europa.eu/eurostat/statistics%20explained/index.php/Learning_mobility_statistics
26. Brendan, O.M.: Education exports worth almost £20 billion to the UK, in University World News (2020)
27. Estermann, T., Pruvot, E.B., Kupriyanova, V., Stoyanova, H.: The Impact of the Covid-19 Crisis on University Funding in Europe: Lessons Learnt from the 2008 Global Financial Crisis. European University Association, Briefing (2020)
28. Lederman, D.: Will shift to remote teaching be boon or bane for online learning. Inside Higher Ed. 18 (2020)
29. Agarwal, N., Srivastava, R., Srivastava, P., Sandhu, J., Singh, P.P.: Multiclass classification of different glass types using random forest classifier. In: 6th International Conference on Intelligent Computing and Control Systems (ICICCS) 2022, pp. 1682–1689. IEEE (2022)

30. Agarwal, N., Singh, V., Singh P.: Semi-supervised learning with GANs for melanoma detection. In: 6th International Conference on Intelligent Computing and Control Systems, ICICCS 2022, pp. 141–147. IEEE (2022)
31. Agarwal, N., Jain, A., Gupta, A., Tayal, DK.: Applying xgboost machine learning model to succor astronomers detect exoplanets in distant galaxies. In: International Conference on Artificial Intelligence and Speech Technology 2021, pp. 385–404. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-95711-7_33